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Impact of Social Media Algorithms on Online Purchasing Decisions

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ABSTRACT

The rapid evolution of social media algorithms has created both opportunities and challenges for online consumer behavior, particularly in relation to purchasing decisions. While algorithms enhance personalization, they also raise concerns about filter bubbles, consumer autonomy, and trust in digital interactions. This study aims to investigate how algorithm-driven personalization, influencer engagement, and recommender systems collectively shape consumer purchase intentions in social commerce environments. To achieve this goal, a mixed-method research design was adopted. The first phase involved a systematic literature review and qualitative expert interviews to construct a conceptual model capturing the interplay between algorithmic personalization, trust, and social influence. The second phase employed a large-scale quantitative survey to validate the model and test hypotheses concerning the effects of algorithmic cues, influencer credibility, and trust-building mechanisms on online purchasing behavior. Findings demonstrate that algorithmic personalization significantly increases consumer engagement and purchase likelihood, but its effectiveness depends strongly on perceived credibility, transparency, and trust. Influencer marketing amplifies these effects by leveraging par asocial interaction and perceived authenticity. However, overexposure to algorithm-driven recommendations can reduce diversity in consumer choices, creating potential long-term risks for both consumers and brands. The study concludes that balancing algorithmic efficiency with transparency and ethical practices is critical for sustainable consumer trust and purchase behavior in digital markets.

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1. Introduction

Over the past decade, the ubiquity of social media platforms has transformed the digital landscape, enabling powerful algorithmic mechanisms to curate content tailored to individual preferences. Social media algorithms dictate the visibility and ordering of posts, advertisements, and recommendations, thereby exerting significant influence over consumers' purchasing decisions. These algorithm-driven environments enable platforms to deliver personalized content based on user behavior, such as likes, shares, and comments—factors demonstrated to shape consumer engagement, trust, and ultimately buying behavior (Arockia Joans Marie Sheila, 2025). In fact, research indicates that approximately %72of consumer purchasing choices are influenced by such algorithmic personalization, and more than half of users believe personalized advertisements directly affect their purchase decisions (Arockia Joans Marie Sheila,.2025).

Moreover, social media algorithms often foster content echo chambers and filter bubbles, restricting users' exposure to diverse viewpoints or products. Such algorithmic structures reinforce user preferences by continually showing similar content, which increases engagement but also limits discovery and critical evaluation (Ge et al., 2020). These echo chambers can thus facilitate impulsive purchases, as repetitive exposure to similar products heightens familiarity and cognitive ease, potentially reducing consumers' deliberation (Ge et al., 2020; Arockia Joans Marie Sheila,2025).

Beyond personalization and exposure dynamics, psychological constructs like parasocial interaction further amplify algorithmic effects. Consumers often form one-sided emotional bonds with influencers through social media interactions a phenomenon known as parasocial interaction which have been found to significantly increase purchase intentions, particularly among younger demographics (Sokolova Kefi, 2019; Xiang et al., 2016). In such cases, algorithmic prioritization of influencer content not only elevates visibility but also leverages trust and attachment to drive purchasing behavior (Sokolova Kefi, 2019). Similarly, influencer marketing more broadly has been shown to shape consumer attitudes and spur impulsive buying by fostering perceived authenticity, credibility, and relatability, which often proves more persuasive than traditional advertising methods (Hollebeek Macky, 2019; Shamim Azam, .2024).

Another key aspect relates to the ethical and aesthetic implications of algorithmic curation. Continuous exposure to visually homogeneous content, driven by algorithmic reinforcement of sameness, may lead to what some researchers describe as "visual exhaustion" a diminished ability to discern novelty and exercise aesthetic judgment, ultimately diminishing consumers' autonomy in decision-making (Portas Mooney, 2024). In such contexts, algorithmic design not only influences purchase behavior but also shapes aesthetic perception and cultural consumption patterns.

Taken together, these algorithmic influences ranging from tailored content exposure and fracturing echo chambers, to parasocial relationships and aesthetic homogenization create an orchestrated pathway by which social media platforms steer online purchasing decisions. Understanding these mechanisms is essential both for scholars investigating consumer behavior and for marketers aiming to adapt strategies in algorithmically-mediated marketplaces.

2. Literature Review

The literature on how social media algorithms shape online purchasing decisions bridges work in recommender systems, digital advertising, electronic word-of-mouth (eWOM), influencer marketing, and consumer psychology, and it converges on a central idea: algorithmic curation alters what consumers see, when they see it, and how social signals are attached to it, thereby reconfiguring the antecedents of attention, preference formation, and choice. Early research on recommender systems established the basic mechanism through which algorithmic filtering personalizes content exposure by predicting user tastes from past behavior and the behavior of similar users (Resnick Varian, 1997). Subsequent empirical and modeling studies showed that such personalization can both increase relevance and inadvertently narrow

the set of options consumers consider, with downstream effects on sales concentration and long-tail consumption (Fleder Hosanagar, 2009). In social media environments where ranking algorithms surface posts, ads, and creator content based on engagement signals, these effects intertwine with social influence processes, amplifying some products while suppressing others in ways that are rarely transparent to end users (Eslami, Rickman, Vaccaro, Aleyasen, Vuong, Karahalios, Hamilton, Sandvig, 2015). Because algorithms serve as de facto gatekeepers of attention, even subtle changes in how they score or order posts can shift the salience of brands, the visibility of promotions, and the perceived popularity of items, producing measurable differences in click-through, carting, and conversion (De Vries, Gensler, Leeflang, 2012; Lambrecht Tucker, .2013)

A foundational path through which algorithms affect purchasing is via social proof, as social media platforms tightly couple recommendation and reputation systems. Classic eWOM studies demonstrated that ratings and reviews causally affect sales by altering perceived quality and risk (Chevalier Mayzlin, 2006; Dellarocas, Zhang, Awad, 2007; Forman, Ghose, Wiesenfeld, 2008). Algorithms magnify these signals by preferentially ranking content with higher engagement, which not only increases exposure to positively signaled products but also triggers feedback loops where visibility begets additional engagement and further uplifts ranking (Aral Walker, 2011). At the same time, algorithmic curation can constrain information diversity, a phenomenon studied in both political and commercial contexts. Work on feed ranking and ideological exposure illustrates how algorithmic sorting shapes the breadth of what users encounter (Bakshy, Messing, Adamic, 2015), and analogous mechanisms appear in commerce when recommender systems repeatedly surface near-neighbors of previously engaged items, narrowing the consideration set and increasing the likelihood of incremental purchases within a category or style (Hosanagar, Fleder, Lee, Buja, 2014). Such narrowing can reduce search costs and enhance satisfaction for consumers with well-defined tastes, yet it may also decrease serendipity and reduce cross-category exploration that stimulates variety seeking and discovery of higher-utility alternatives (Fleder Hosanagar, 2009; Ricci, Rokach, Shapira, .2011) .

A second pathway involves personalization in paid advertising and its interaction with organic algorithmic ranking. Research in quantitative marketing documents that ad relevance, when aligned to user interests and stage in the purchase funnel, boosts persuasion, but that excessive or ill-timed targeting can backfire by eliciting privacy concerns or reactance (Goldfarb Tucker, 2011; Aguirre, Mahr, Grewal, de Ruyter, Wetzels, 2015). Dynamic retargeting—ads served based on a consumer's prior product views—tends to be more effective when product preferences are stable and category fit is high, while more abstract, category-level ads perform better in early stages (Lambrecht Tucker, 2013). Algorithms that decide which ad to show and to whom are further conditioned by platform engagement metrics, so the same user may be exposed to sequences of messages that the system infers will maximize predicted click-through; the cumulative effect can subtly shift preferences through mere exposure, familiarity, and availability heuristics (Bleier Eisenbeiss, 2015; Aribarg Foutz, 2009). Importantly, studies indicate that the perceived appropriateness of personalization moderates outcomes: when consumers perceive targeting as diagnostic and helpful, ad effectiveness rises; when it feels intrusive or opaque, trust declines and avoidance increases (Aguirre et al., 2015; Bleier Eisenbeiss, 2015). Because social media interfaces interleave ads with organic posts and influencer content, users may not always differentiate between paid and unpaid persuasion, further blurring the route by which algorithmic choices translate into purchase intent (Tucker,.2014) .

Influencer marketing represents a third, distinctive channel where algorithmic ranking and social cognition jointly shape purchasing. Work in advertising and consumer behavior shows that perceived credibility, attractiveness, and parasocial interaction with influencers mediate the impact of endorsements on brand attitudes and purchase intentions (De Veirman, Cauberghe, Hudders, 2017; Sokolova Kefi, 2020; Djafarova Rushworth, 2017). Algorithms help determine which influencers' content is surfaced and when;

thus, the effective reach and persuasion of an endorsement are not merely a function of follower counts but also of how the platform scores each post for predicted engagement and relevance (De Vries et al., 2012). Evidence suggests that micro-influencers can outperform celebrity endorsers in conversion when their audiences perceive higher authenticity and when content-platform fit is strong, especially in visually oriented categories such as fashion and beauty (De Veirman et al., 2017; Sokolova Kefi, 2020). Because algorithmic signals are often derived from early engagement, tactical decisions about posting time, creative elements, and call-to-action formatting can trigger positive feedback loops that propel content into recommendation slots and explore/exploit cycles, amplifying purchase-relevant exposure (De Vries et al., 2012). In turn, brands adapt their creative and seeding strategies to these algorithmic affordances, designing content to maximize predicted ranking rewards—shorter hooks, high-velocity interactions in the first minutes, and iterative A/B variants—thus co-evolving persuasion with platform incentives (Aral Walker, 2011; Tucker, .2014).

The literature also underscores the role of peer networks and contagion in algorithmically mediated purchasing. A core challenge in observational studies is separating homophily (similar people choose similarly) from true peer influence (one person's action causes another's action). Methodological advances leveraging randomized encouragement designs and network instrumentation demonstrate that exposure to peers' actions in feed interfaces causally increases adoption and purchases, though effects vary by tie strength and product category (Aral, Muchnik, Sundararajan, 2009; Aral Walker, 2011). Social media algorithms, by prioritizing content likely to elicit social feedback, tend to emphasize posts from strong ties and high-engagement nodes, which can heighten contagion for hedonic, identity-expressive products where social signaling is salient (Aral Walker, 2011). At the same time, rankers can compress the tail of weak-tie exposure that is often conducive to discovering novel or niche products, potentially reducing cross-cluster innovation diffusion that supports category growth (Bakshy et al., 2015; Hosanagar et al., 2014). This asymmetry matters for firms: while ranking that accentuates strong-tie reinforcement may lift short-run conversions within established segments, it can slow penetration into new segments unless complemented by paid distribution or creator collaborations that deliberately cross network boundaries (Aral Walker, 2011; De Veirman et al., 2017).

Another body of research interrogates diversity, fairness, and bias in algorithmic recommendation and their consequences for consumer welfare. Modeling and field evidence indicate that recommender systems can either increase or decrease sales diversity depending on how they balance popularity against user-item fit; popularity-biased rankers funnel attention to already successful items, while diversity-aware designs can expand the set of items receiving exposure (Fleder Hosanagar, 2009; Hosanagar et al., 2014). In commerce, lower diversity can translate into less competitive pressure and higher prices or narrower choice sets for consumers, while higher diversity may enhance perceived autonomy and post-purchase satisfaction through better preference matching (Ricci et al., 2011). Empirical work on feed transparency shows that users often misunderstand why certain posts appear, and that disclosure about ranking logic can recalibrate expectations and reduce misattributions of manipulation; however, the effects of transparency on engagement and monetization are mixed, indicating a trade-off platforms face between explainability and performance (Eslami et al., 2015). For vulnerable consumers, including adolescents and individuals with compulsive buying tendencies, heavy personalization and infinite-scroll designs may intensify impulsivity and diminish self-control, heightening the risk of regret and financial harm in contexts that algorithmically foreground limited-time offers, scarcity cues, or socially validated trends (Verhagen van Dolen, 2011; Dholakia, 2000). These findings feed into an emerging debate about ethical recommender design and the need for guardrails that protect consumer welfare without eliminating the benefits of relevance (Aguirre et al., 2015; Hosanagar et al.2014).

A critical intersection of algorithms and consumer psychology appears in the timing and sequence of exposures. Mere exposure effects suggest that repeated encounters with a stimulus increase liking and choice probability, especially when exposures are spaced and embedded in varied contexts (Bornstein, 1989). Social media rankers inherently schedule repeated exposures to similar content as users continue interacting with a theme, and ad delivery systems use frequency caps and pacing algorithms to distribute impressions across time. Field experiments in digital advertising show inverted-U relationships where moderate repetition increases conversion but overexposure triggers fatigue and avoidance (Bleier Eisenbeiss, 2015). Retargeting studies add that reminder ads work best immediately after product consideration and lose effectiveness as time since last interaction grows or as the consumer advances past the decision point (Lambrecht Tucker, 2013). When these temporal dynamics are aligned with social signals (e.g., a friend recently liked a product), effects compound: consumers are more responsive to ads or posts that combine personal relevance with proximate social endorsement, reinforcing the algorithm's tendency to weight social and recency signals in ranking (Aral Walker, 2011)

Trust and perceived risk remain central moderators of algorithmic impact on purchasing. In e-commerce, trust in the vendor and in the medium reduces perceived risk and facilitates transaction completion (Gefen, 2000; McKnight, Choudhury, Kacmar, 2002). On social platforms, trust operates at multiple layers: trust in the influencer, in the platform's curation, and in the advertiser. Studies show that disclosures (e.g., "sponsored") can reduce persuasion by highlighting persuasive intent, but they can also preserve trust when they clarify the nature of the relationship, with net effects depending on prior attitudes and the influencer's authenticity (De Veirman et al., 2017; Sokolova Kefi, 2020). Algorithmic opacity can erode trust when users suspect manipulation, yet perceived personalization can restore it when recommendations feel tailored and beneficial (Aguirre et al., 2015). Brands that align creative with platform norms—visual storytelling in image-centric feeds, short-form vertical videos in algorithmic "For You" streams—tend to benefit because the algorithms reward native formats, which users interpret as less interruptive and more trustworthy content (De Vries et al., 2012).

The literature also connects algorithmic curation to price sensitivity and promotional responsiveness. When rankers surface limited-time deals or "trending" items, they overlay scarcity and herding cues on top of product information, reducing perceived search time and increasing urgency. Research on demand under scarcity and social proof indicates that such cues can shift consumers from deliberative to heuristic processing, increasing the probability of impulse purchases and lowering elasticity in the moment (Dholakia, 2000; Verhagen van Dolen, 2011). Because algorithms learn from conversion events, successful promotions can create self-reinforcing cycles where items flagged as "popular" receive more impressions, amplifying the lift beyond the intrinsic price effect (Hosanagar et al., 2014). However, if the algorithm prioritizes short-term conversion probability over long-term satisfaction, it may encourage purchases that lead to higher return rates or negative post-purchase word-of-mouth, outcomes that are rarely visible to the ranking objective but matter for consumer welfare and brand equity (Aguirre et al., 2015). This misalignment raises calls in the literature for multi-objective recommendation that balances conversion with satisfaction and diversity (Ricci et al., 2011).

Scholars have also examined creative attributes and engagement metrics that feed ranking systems. Analyses of brand content on social platforms reveal that vividness (e.g., video), interactivity (polls, questions), and information value all increase engagement, and that early engagement velocity is a strong predictor of subsequent reach because of the algorithm's exploitation of promising posts (De Vries et al., 2012). For commerce-adjacent content, value-adding posts that educate or entertain often secure deeper engagement than purely promotional posts, indirectly elevating the organic reach of later promotional messages to the same audience through the ranker's accumulated affinity signals (De Vries et al., 2012). In influencer contexts, authenticity cues—behind-the-scenes footage, personal narratives, consistent

aesthetics—have been linked to higher intentions to purchase the endorsed products, again mediated by parasocial interaction and perceived fit between influencer and product category (Sokolova Kefi, 2020; Djafarova Rushworth, 2017). These creative and relational factors are not independent of algorithms; rather, they are endogenous responses to the reward structure that the algorithms impose, illustrating the co-adaptation of marketers and platforms that the literature increasingly highlights (Aral Walker, 2011).

A persistent methodological challenge in the field is causal identification amid complex feedback loops. Many studies rely on natural experiments, field experiments, or instrumented randomized trials to separate the effects of algorithmic exposure from selection. For instance, randomized ad delivery or recommendation variations enable measurement of lift attributable to specific targeting features or ranking thresholds (Goldfarb Tucker, 2011; Lambrecht Tucker, 2013). Network experiments that vary social cues or peer exposure help isolate contagion from homophily (Aral et al., 2009; Aral Walker, 2011). Mixed-method studies that pair behavioral data with interviews reveal how users make sense of algorithmic feeds often incorrectly and how these mental models inform their receptivity to commerce content (Eslami et al., 2015). The accumulation of such evidence supports a nuanced view: algorithms are neither uniformly manipulative nor uniformly empowering; their effects depend on design choices, user goals, product types, and the social context in which exposure occurs.

From a managerial perspective, the literature implies that firms need to design for algorithmic compatibility while safeguarding consumer trust and choice quality. Targeting and creative should reflect the stage of the consumer journey and the platform's ranking incentives, leveraging diagnostic cues and value-adding content to earn organic reach (Bleier Eisenbeiss, 2015; De Vries et al., 2012). Retargeting should be time-bounded and sensitive to signals of decision completion to avoid reactance (Lambrecht Tucker, 2013). Collaborations with influencers should prioritize fit and authenticity over raw reach, and should consider posting strategies that seed early engagement to trigger algorithmic amplification (De Veirman et al., 2017; Sokolova Kefi, 2020). At the same time, attention to diversity and exploration can help brands avoid overfitting to narrow segments, building long-term equity by exposing consumers to adjacent categories in ways that feel serendipitous rather than pushy (Fleder Hosanagar, 2009; Hosanagar et al., 2014). For platforms and policymakers, the research suggests that transparency mechanisms, user controls, and multi-objective ranking could mitigate harms while preserving the benefits of personalization, though careful experimentation is needed to avoid unintended reductions in relevance or engagement (Eslami et al., 2015).

In sum, the literature converges on several integrative propositions. First, algorithmic curation in social media systematically reconfigures the consumer's consideration set by blending personalized relevance with socially constructed signals of popularity and endorsement, thereby affecting both the probability and the timing of purchase (Resnick Varian, 1997; Chevalier Mayzlin, 2006; Aral Walker, 2011). Second, paid and organic pathways interact within the same ranking substrates, so that effectiveness depends on perceived appropriateness of personalization, creative-platform fit, and the orchestration of exposure sequences (Goldfarb Tucker, 2011; Lambrecht Tucker, 2013; Bleier Eisenbeiss, 2015). Third, algorithmic choices about popularity bias, diversity, and transparency carry welfare implications: they can streamline search and boost satisfaction when aligned with user goals, but they can also narrow choice and encourage impulsivity when optimized solely for engagement or short-run conversion (Fleder Hosanagar, 2009; Hosanagar et al., 2014; Verhagen van Dolen, 2011). Finally, because user behavior, creator strategies, and platform algorithms co-evolve, effects are dynamic rather than static, underscoring the value of ongoing experimentation and theory that integrates information systems design with consumer psychology and network economics (Aral et al., 2009; Eslami et al., 2015). Collectively, this body of work explains how the interplay of personalization, social influence, and platform incentives renders social media algorithms powerful shapers of modern purchasing behavior, illuminating both opportunities for improved relevance and risks to autonomy that future research and practice must address .

3. Research Methodology

The methodological framework for this research has been designed to capture both the exploratory and confirmatory dimensions of understanding the impact of social media algorithms on online purchasing decisions. A mixed-methods approach is adopted in order to combine the depth and richness of qualitative insights with the generalizability and statistical rigor of quantitative techniques. This design aligns with established methodological traditions in marketing and information systems research that emphasize triangulation to strengthen validity and reliability (Creswell Plano Clark, 2011). The methodological structure unfolds in two major phases: first, the conceptual development of a model based on extant literature and qualitative exploration through expert insights, and second, a large-scale empirical validation of the model through quantitative techniques. This phased structure ensures that theoretical constructs are not only grounded in prior scholarship but also informed by practitioner perspectives, followed by robust empirical testing with consumer samples. The choice of a sequential exploratory design is consistent with research on emerging technological phenomena, where constructs may not be fully established in existing theory and require iterative refinement before hypothesis testing (Venkatesh, Brown, Bala, 2013). Therefore, the methodology has been purposefully crafted to balance theory-building with theory-testing, addressing both academic contributions and managerial implications.

- **Phase 1: Conceptual Model Development and Qualitative Exploration**

The first phase is concerned with inductive exploration and conceptual clarity, as the constructs related to algorithmic influence on purchasing decisions are multidimensional and intersect disciplines such as consumer psychology, information systems, and marketing. This phase involves two complementary strategies: a systematic literature review and expert interviews. The rationale for starting with conceptual development stems from the fact that existing literature treats personalization, influencer marketing, and social commerce in fragmented silos, whereas algorithmic mediation cuts across these domains. By synthesizing prior work and combining it with experiential knowledge of practitioners, a comprehensive conceptual model can be articulated that specifies antecedents, mediators, and outcomes of algorithmic influence in social commerce. This iterative process of refinement ensures face validity and theoretical robustness (Eisenhardt, 1989). The use of qualitative inquiry at this stage is not only to generate propositions but also to sharpen construct operationalization, paving the way for survey-based validation in the second phase.

- **Systematic Literature Review (SLR)**

The systematic literature review follows a structured protocol designed to ensure comprehensiveness, transparency, and replicability (Tranfield, Denyer, Smart, 2003). Database searches were conducted across Scopus, Web of Science, and ABI/INFORM using combinations of keywords such as “social media algorithms,” “online purchasing behavior,” “recommender systems,” “influencer marketing,” and “digital personalization.” The inclusion criteria targeted peer-reviewed journal articles published between 2000and 2023in marketing, information systems, psychology, and communication journals. Exclusion criteria involved conference abstracts, non-English publications, and studies without empirical or theoretical contributions. The initial search yielded over 1,200articles, which were reduced to 180after screening for relevance and quality. The selected studies were coded along dimensions such as conceptual focus (personalization, social proof, trust, impulsivity), methodological approach (survey, experiment, big data analysis), and theoretical framework (e.g., Technology Acceptance Model, Persuasion Theory, Stimulus-Organism-Response). This coding process revealed several research gaps: limited integration across personalization and influencer streams, scarce attention to long-term consumer welfare outcomes, and underexplored mechanisms of algorithmic opacity and trust. Synthesizing these insights, the review informs a conceptual model in which algorithmic curation shapes purchase intention through mediating constructs such as trust, parasocial interaction, and perceived relevance, moderated by consumer traits like privacy

concerns and impulse buying tendency. This literature synthesis thus provides a theoretically grounded yet innovation-oriented basis for subsequent empirical work.

- **Expert Interviews**

To complement the SLR, semi-structured interviews with domain experts were conducted to capture experiential insights and practitioner-driven perspectives on how social media algorithms influence consumer decision-making. The experts included marketing managers, data scientists working with recommender systems, and digital strategy consultants with direct experience in social commerce. A purposive sampling approach was used to identify 15experts across diverse industries such as fashion, consumer electronics, and online retail. Interviews lasted between 45and 75minutes, were recorded and transcribed verbatim, and analyzed using thematic coding (Braun Clarke, 2006). The interview guide covered topics such as algorithmic personalization strategies, consumer engagement metrics, perceived effectiveness of influencer campaigns, and ethical concerns regarding transparency. Analysis revealed converging themes with the literature, particularly around the power of algorithms to amplify influencer credibility and to create echo chambers of product exposure. At the same time, experts emphasized novel dimensions less developed in prior scholarship, such as the role of algorithmic volatility in disrupting campaign outcomes, the challenge of balancing engagement maximization with consumer trust, and the managerial need for adaptive creative strategies that align with algorithmic preferences. These insights informed refinement of constructs like "algorithmic visibility," "perceived fairness of curation," and "trust calibration," which were subsequently integrated into the conceptual model. Thus, expert interviews provided ecological validity, practical nuance, and construct enrichment beyond what could be distilled from published research alone.

- **Phase 2: Quantitative Model Validation and Hypothesis Testing**

The second phase moves from exploration to validation, employing quantitative methods to test hypotheses derived from the conceptual model. The primary aim is to establish causal pathways and examine moderating effects at scale using consumer-level data. Structural equation modeling (SEM) was chosen as the analytic approach because it allows for simultaneous testing of multiple relationships, accommodates latent constructs, and provides assessment of model fit (Hair, Black, Babin, Anderson, 2010). Hypotheses were operationalized to test whether algorithmic personalization and influencer visibility predict online purchase intentions through mediators such as trust, parasocial interaction, and perceived relevance, with moderators such as privacy concern and impulsivity. Sampling involved targeting active social media users aged 18–45, recruited through stratified random sampling to ensure diversity in demographics and platform usage. Power analysis determined that a sample of at least 400respondents would be required to detect medium effects with adequate statistical power at $p < 0.05$. Data collection was conducted online, with strict controls for attention checks and response quality. Ethical approval was obtained, and participants were assured of anonymity and voluntary participation. This quantitative phase not only tests theory-driven hypotheses but also provides generalizable insights that complement the conceptual exploration of phase one, creating a robust methodological synergy.

- **Survey Design and Instrumentation**

Survey design was informed by both the systematic literature review and expert interviews, ensuring that items reflect established scales while adapting to the unique context of social media algorithms. Measurement scales were drawn from validated sources in the literature: trust scales adapted from McKnight, Choudhury, and Kacmar (2002); parasocial interaction scales from Rubin, Perse, and Powell (1985); personalization perception scales from Xu (2007); and impulsive buying tendency measures from Verplanken and Herabadi (2001). All items were measured using seven-point Likert scales ranging from strongly disagree to strongly agree. Pretesting of the survey was conducted with 30respondents to evaluate clarity, length, and reliability, resulting in minor modifications to wording and layout. Construct validity

was ensured through confirmatory factor analysis (CFA), while reliability was assessed with Cronbach's alpha, aiming for thresholds above 0.7. To mitigate common method bias, procedural remedies such as temporal separation of predictor and outcome measures and inclusion of reverse-coded items were employed (Podsakoff, MacKenzie, Lee, Podsakoff, 2003). The final survey included sections on demographic characteristics, social media usage habits, perceptions of algorithmic personalization, trust in influencers and platforms, parasocial interaction experiences, and recent purchasing behavior influenced by social media. Data collection utilized online panels with quotas to match population distributions in age and gender. This rigorous instrumentation ensured that the quantitative model was tested on robust, reliable, and valid data, thereby enhancing the credibility of findings and enabling meaningful theoretical and managerial implications.

4- Findings

- **Insights from Systematic Literature Review**

The systematic literature review yielded a detailed understanding of how algorithms embedded in social media platforms influence consumers' online purchasing decisions. Across 180high-quality peer-reviewed articles screened and synthesized, three principal domains emerged: algorithmic personalization and recommender systems, social influence and influencer marketing, and digital consumer psychology. Within the first domain, studies consistently showed that algorithmic ranking increases relevance by presenting products aligned with past preferences and predicted interests. Such personalization reduces search costs, enhances convenience, and fosters perceptions of efficiency in shopping processes (Ricci, Rokach, Shapira, 2011). For example, Fleder and Hosanagar (2009) demonstrated that recommender systems channel demand toward a concentrated set of products, thereby creating both benefits in relevance and drawbacks in reduced variety. Similarly, Hosanagar, Fleder, Lee, and Buja (2014) identified the tendency of personalization to create "algorithmic echo chambers," where consumers repeatedly encounter the same categories, limiting discovery and exploration. This duality underscores a trade-off between immediate conversion and long-term satisfaction.

The second stream concentrated on influencer marketing, parasocial interaction, and credibility. Influencers' effectiveness is not simply a product of their reach but is strongly mediated by authenticity and perceived closeness to audiences (De Veirman, Cauberghe, Hudders, 2017). Social media algorithms play a decisive role by boosting posts with early engagement, thereby amplifying credibility signals and strengthening parasocial bonds (Sokolova Kefi, 2020). Importantly, the literature highlights that micro-influencers with niche content often achieve higher purchase conversion compared to celebrities when their content resonates algorithmically with a specific audience segment. This finding reveals that algorithms act as gatekeepers of persuasion by determining which endorsements gain visibility.

The third domain revolved around consumer psychology constructs such as trust, privacy concern, impulsivity, and fairness perception. Aguirre, Mahr, Grewal, de Ruyter, and Wetzels (2015) showed that personalization is effective when consumers interpret it as relevant and useful but counterproductive when perceived as intrusive or manipulative. Verhagen and van Dolen (2011) demonstrated that algorithmically enhanced cues like trending tags or scarcity signals increase the likelihood of impulse purchases. Taken together, these findings underscore that algorithms influence consumers not only through exposure but also through psychological framing, shaping perceptions of trustworthiness, urgency, and authenticity.

The literature review therefore confirmed the validity of a research model that includes algorithmic personalization and influencer visibility as independent variables, trust, parasocial interaction, and perceived relevance as mediators, and privacy concern and impulsivity as moderators influencing online purchase intention. It also revealed gaps, particularly the lack of integration between personalization and influencer marketing literature, limited exploration of long-term consumer outcomes, and insufficient

theorization of algorithmic opacity. These gaps provided the rationale for expert interviews and quantitative hypothesis testing in subsequent phases

- **Themes from Expert Interviews**

The qualitative phase, based on 15in-depth semi-structured expert interviews with marketing managers, digital strategists, and recommender system designers, enriched the conceptual model by introducing practitioner-based nuances often absent from the literature. Thematic analysis of interview transcripts generated several prominent themes. First, experts emphasized the volatility of algorithms as a determinant of campaign effectiveness. Unlike static advertising media, social media algorithms continuously adjust based on engagement, leading to unpredictable amplification or suppression of content. Several experts described how identical content pieces could perform dramatically differently depending on early interactions within the first hours of posting. This reinforces the importance of early engagement velocity as a driver of visibility, consistent with the literature but elaborated with richer managerial insight.

Second, interviewees repeatedly discussed the centrality of trust and fairness perception in sustaining consumer engagement. While personalization was viewed as enhancing convenience, experts cautioned that consumers quickly perceive over-targeting as invasive, particularly in cases of repeated retargeting after a single product view. The balance between helpfulness and intrusiveness was identified as a delicate line that marketers must navigate carefully. One expert described it as a "trust equilibrium," where each positive instance of helpful personalization strengthens the relationship, while each instance of overexposure or irrelevance erodes it.

Third, influencers were described as "algorithmic amplifiers," whose visibility is inseparable from platform curation. Experts agreed that algorithmic mediation determines whether an endorsement becomes widely influential or fades into obscurity. A recurring insight was the role of micro-influencers, who often achieve higher authenticity and conversion, provided the algorithm surfaces their content to relevant audiences. Experts highlighted that algorithmic opacity complicates planning: marketers design strategies without knowing precisely which signals the algorithm prioritizes, leading to a process of constant experimentation.

Fourth, ethical concerns were strongly emphasized. Experts raised issues around manipulation, compulsive consumption, and the potential harm of algorithmic reinforcement of impulsive buying tendencies, particularly among younger consumers. Several stressed the need for more transparent communication to consumers about why certain ads or products are shown.

Overall, expert interviews confirmed the conceptual model derived from the literature but added nuanced constructs such as algorithmic volatility, fairness calibration, and managerial adaptation strategies. These findings guided the design of survey instruments and informed the operationalization of constructs such as algorithmic visibility and trust calibration.

- **Quantitative Model Validation**

The quantitative phase tested the conceptual model through a large-scale survey of 427social media users aged 18–45, analyzed using structural equation modeling (SEM). Measurement models underwent confirmatory factor analysis (CFA), establishing strong construct validity with factor loadings above 0.70 and composite reliability exceeding 0.80for all latent variables. Discriminant validity was confirmed using Fornell-Larcker criteria. Model fit indices indicated strong overall fit ($\chi^2/df = 2.31$; CFI = 0.94; TLI = 0.93; RMSEA = 0.054). These metrics confirmed that the hypothesized constructs were empirically distinct and adequately measured.

Descriptive statistics revealed that respondents reported high levels of social media use, with %76 indicating that they encounter product-related content daily. More than half reported having made at least one purchase in the last month directly influenced by social media exposure. Trust in platforms, trust in influencers, and perceived personalization all scored above the midpoint of the scale, suggesting that

participants generally recognize value in algorithmically mediated experiences, although privacy concern also scored relatively high, indicating ambivalence.

Path analysis demonstrated that algorithmic personalization significantly predicted perceived relevance ($\beta = 0.46$, $p < .001$) and trust ($\beta = 0.32$, $p < .01$). Influencer visibility significantly predicted parasocial interaction ($\beta = 0.54$, $p < .001$) and trust ($\beta = 0.38$, $p < .001$). Both trust ($\beta = 0.41$, $p < .001$) and parasocial interaction ($\beta = 0.35$, $p < .001$) significantly predicted online purchase intention. Perceived relevance also had a positive effect ($\beta = 0.29$, $p < .01$). Moderation tests revealed that privacy concern negatively moderated the effect of personalization on trust ($\beta = -0.18$, $p < .05$), while impulsivity positively moderated the relationship between perceived relevance and purchase intention ($\beta = 0.22$, $p < 0.05$).

Multi-group analysis by age group revealed stronger effects of parasocial interaction on purchase intention among younger consumers (18–25) compared to older cohorts (26–45), suggesting that younger users are more influenced by algorithmically amplified influencer relationships. Gender-based analysis indicated that women reported higher parasocial interaction scores and stronger trust in influencers, whereas men showed higher sensitivity to personalization relevance.

Together, these findings empirically validated the conceptual model. They confirmed the central roles of trust, parasocial interaction, and relevance as mediators, while also demonstrating the moderating influence of privacy concern and impulsivity. Importantly, the quantitative data corroborated qualitative insights from expert interviews, such as the fragility of trust and the heightened responsiveness of younger demographics to influencer-driven persuasion.

- **Hypothesis Testing Results**

Hypothesis testing results provided detailed confirmation of the proposed model. Hypothesis 1, which posited that algorithmic personalization positively influences perceived relevance, was supported with strong significance ($\beta = 0.46$, $p < .001$). Hypothesis 2, suggesting a positive relationship between personalization and trust, was also supported ($\beta = 0.32$, $p < .01$), though moderation by privacy concern (H2a) indicated that this effect diminishes when consumers report high concern about data use. Hypothesis 3, predicting that influencer visibility positively influences parasocial interaction, received robust support ($\beta = 0.54$, $p < .001$). Hypothesis 4, which posited that influencer visibility enhances trust, was likewise supported ($\beta = 0.38$, $p < 0.01$).

Hypotheses 5, 6, and 7concerned mediation effects. Trust significantly mediated the effect of personalization and influencer visibility on purchase intention, consistent with prior findings that trust is central in online commerce (McKnight, Choudhury, Kacmar, 2002). Parasocial interaction also mediated the effect of influencer visibility on purchase intention, highlighting the psychological mechanisms of perceived intimacy and authenticity. Perceived relevance partially mediated the link between personalization and purchase intention, confirming that relevance is both a direct and indirect predictor.

Hypothesis 8proposed that privacy concern moderates the personalization–trust relationship. This was confirmed, with high privacy concern weakening the effect of personalization on trust. Hypothesis 9 proposed that impulsivity moderates the relevance–purchase intention relationship, which was also confirmed, indicating that highly impulsive consumers are more likely to translate perceived relevance into immediate purchasing behavior.

Overall, the hypothesis testing results provide strong support for the conceptual model. They reveal that algorithmic personalization and influencer visibility indirectly drive online purchase intention through psychological mediators, and that these effects are contingent on consumer traits. The integration of qualitative and quantitative findings underscores the robustness of the results, suggesting that while algorithms can be powerful tools for increasing conversions, their effectiveness is mediated by consumer perceptions of trust, fairness, and authenticity.

5- Discussion and Conclusion

The findings of this research provide substantial insights into how social media algorithms are fundamentally shaping online consumer purchasing decisions and the broader implications of these mechanisms for marketing practice, consumer welfare, and digital platform governance. The synthesis of systematic literature review, expert interviews, and quantitative survey validation produced a multi-layered understanding that enriches both theoretical perspectives and managerial applications. At the center of the discussion lies the recognition that algorithmic personalization and influencer visibility are not merely technical tools of content distribution but are deeply embedded socio-technical systems that influence consumer cognition, emotions, and behaviors in ways that are subtle, complex, and often opaque. By drawing on the integrated evidence base, this section elaborates the implications of the results, links them to existing literature, reflects on theoretical contributions, outlines practical implications for marketers and policymakers, and highlights directions for future research, all while arriving at a coherent conclusion about the role of algorithms in shaping the evolving landscape of digital commerce.

The evidence from the study confirmed that algorithmic personalization is one of the strongest predictors of perceived relevance, trust, and ultimately purchase intention. This supports the dominant argument in the literature that relevance-enhancing mechanisms create efficiency and convenience for consumers, thereby facilitating transactional behaviors in digital environments. However, the findings also demonstrate that these benefits are conditional and moderated by factors such as privacy concern. When consumers perceive personalization as intrusive or manipulative, the positive effect of algorithms on trust is diminished or even reversed. This duality highlights a critical tension between utility and surveillance: consumers appreciate personalization when it simplifies their decision-making, but they simultaneously fear the exploitation of their personal data. This tension contributes to what can be termed a personalization paradox, in which the very features that increase relevance and efficiency also risk undermining trust if deployed without sensitivity to consumer expectations of fairness and transparency. Such paradoxical dynamics echo prior discussions in consumer research about the trade-offs inherent in targeted advertising, but the present findings extend these discussions by quantifying the moderating role of privacy concern and by emphasizing that trust calibration is not static but fluctuates across different consumer segments and contexts.

Similarly, the role of influencers, mediated by algorithmic visibility, reveals the profound interplay between technology and psychology in shaping purchasing behaviors. The evidence that parasocial interaction significantly mediates the relationship between influencer visibility and purchase intention confirms the argument that social bonds—whether real or imagined—play a decisive role in persuasion. What this research contributes to the literature is a more nuanced understanding of how algorithmic amplification interacts with parasocial processes. Algorithms do not merely reflect popularity but actively create it by rewarding early engagement signals, thereby granting influencers amplified visibility and reinforcing their perceived authenticity. The combination of algorithmic amplification with parasocial intimacy produces a powerful mechanism for driving purchase intention, particularly among younger consumers who report stronger identification with influencers. This points to the evolving nature of advertising where traditional markers of celebrity endorsement are displaced by micro-influencers whose authenticity is algorithmically amplified, creating a complex network of relational persuasion that is both more intimate and more technologically mediated than prior forms of marketing communication.

The findings also point to the centrality of trust as a mediating construct across both personalization and influencer visibility. Trust functions not merely as a static evaluation but as a dynamic psychological state continuously shaped by consumer-platform and consumer-influencer interactions. The evidence suggests that each successful instance of relevant personalization or authentic influencer endorsement strengthens trust, while each instance of perceived manipulation or irrelevance erodes it. This dynamic nature of trust

resonates with broader theoretical discussions in information systems and consumer behavior, where trust is increasingly seen as fragile, context-dependent, and easily undermined. Importantly, the results of this research confirm that trust remains one of the most powerful predictors of online purchasing intention, highlighting the need for marketers to prioritize strategies that sustain and calibrate trust over time.

The discussion must also consider the role of consumer traits such as impulsivity and privacy concern. The moderating effect of impulsivity on the relevance-purchase link indicates that algorithms may disproportionately influence consumers with higher impulsive tendencies, potentially raising ethical concerns about exploitation and compulsive buying behaviors. The reinforcement of impulsivity through features such as infinite scroll, trending badges, or limited-time offers raises normative questions about whether platforms should bear responsibility for curbing manipulative design practices that exploit psychological vulnerabilities. This concern intersects with debates on digital well-being and consumer protection, suggesting that the governance of algorithms should extend beyond commercial effectiveness to include considerations of long-term consumer welfare. Similarly, the moderating role of privacy concern illustrates that consumer heterogeneity significantly shapes the effectiveness of algorithmic strategies. Platforms that fail to account for such heterogeneity risk alienating privacy-sensitive consumers, which could undermine long-term loyalty and brand equity.

From a theoretical standpoint, the study contributes by integrating personalization and influencer marketing literatures, which have often evolved in parallel but rarely intersected. The integrated model demonstrates that algorithms influence consumers through both cognitive pathways (perceived relevance and trust) and affective pathways (parasocial interaction and intimacy with influencers). This dual-pathway framework offers a more holistic understanding of how digital persuasion operates, bridging gaps between recommender system research, consumer psychology, and marketing communication. Furthermore, the introduction of constructs such as algorithmic volatility, drawn from expert interviews, enriches theoretical discourse by emphasizing the dynamic and unpredictable nature of algorithmic mediation. Theoretical models that treat algorithms as static systems risk underestimating their dynamic adaptivity and the implications of such volatility for consumer outcomes.

For practitioners, the implications are multifaceted. Marketers must recognize that algorithmic personalization is not a one-size-fits-all tool but requires careful calibration to avoid breaching consumer trust. Designing strategies that balance helpfulness with respect for privacy is essential. For instance, offering transparent explanations for why specific recommendations are shown could enhance perceived fairness and mitigate intrusiveness. Similarly, influencer marketing strategies must adapt to algorithmic dynamics by prioritizing authenticity and engagement velocity rather than follower count alone. Brands that collaborate with micro-influencers and foster genuine interaction are more likely to benefit from algorithmic amplification, thereby driving higher purchase conversion. At the same time, practitioners must remain mindful of ethical considerations, avoiding strategies that exploit consumer impulsivity or create unhealthy dependencies on algorithmically mediated consumption.

From a policy perspective, the findings highlight the urgency of developing clearer guidelines for algorithmic transparency and accountability. As algorithms increasingly mediate commercial persuasion, regulatory frameworks should ensure that consumers are not misled or manipulated in ways that compromise their autonomy. Policies requiring platforms to disclose the logic of personalization, allow users to control the degree of algorithmic influence, or limit manipulative design features could help restore balance between commercial effectiveness and consumer welfare. This aligns with ongoing discussions in digital ethics and platform governance, where scholars and regulators are calling for a “responsible personalization” framework that safeguards consumer rights without undermining innovation.

Despite its contributions, this research also has limitations that suggest avenues for future inquiry. While the quantitative model was validated through a sizable sample, the generalizability of findings may be

limited to specific cultural and demographic contexts. Future research should test the model across diverse cultural settings to examine whether perceptions of personalization, trust, and influencer credibility vary cross-culturally. Additionally, while this study captured consumer perceptions at a particular point in time, algorithms and consumer attitudes are highly dynamic. Longitudinal research could offer richer insights into how the personalization paradox and trust calibration evolve over time. Experimental designs could also be employed to directly manipulate algorithmic visibility and personalization to observe causal effects on consumer decision-making. Moreover, future work should investigate long-term outcomes, including whether algorithmically induced purchases lead to sustained satisfaction, loyalty, or regret. Addressing these gaps would contribute to a more comprehensive understanding of the enduring impacts of algorithmic mediation on consumer behavior.

In conclusion, this research provides robust evidence that social media algorithms significantly shape online purchasing decisions through mechanisms of personalization, influencer visibility, trust, parasocial interaction, and perceived relevance, moderated by consumer traits such as privacy concern and impulsivity. The findings highlight the paradoxical nature of personalization, the powerful interplay of algorithms and parasocial bonds, and the dynamic fragility of trust as central to digital commerce. By integrating insights from literature, practitioner perspectives, and quantitative validation, the study contributes to theory by bridging disparate research streams and to practice by offering actionable strategies for marketers. It also raises important ethical and policy considerations regarding the exploitation of consumer vulnerabilities and the need for transparency in algorithmic design. Ultimately, the discussion underscores that algorithms are not neutral tools but active participants in shaping consumer markets, social relationships, and individual well-being. As digital platforms continue to evolve, the challenge for scholars, practitioners, and policymakers alike is to harness the persuasive power of algorithms responsibly, ensuring that the future of commerce balances efficiency and profitability with fairness, autonomy, and consumer welfare.

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